## time\_dependent\_gillespie

April 28, 2020

## 0.1 Time Dependent Gillespie Algorithm

In this notebook, we provide a numerical implementation of our Gillespie Algorithm, for two contact rate models. The first considers a simple exponential rate (which is not used in the report) and a cyclical contact rate which is used.

```
In [149]: import numpy as np
    import matplotlib.pyplot as plt
    import pandas as pd
    from scipy import optimize
```

## 0.2 1 - Exponential Decay Contact Rate Model (Not used in report)

Please see the notebook titled "exponential\_contact\_mode.ipynb" for implementation of the exponential model that is discussed in our report.

 $B(t) = Ae^{-\alpha t}$ 

Here we consider the contact rate:

return A

return A\*np.exp(-a\*t)

```
def cosine_rate(t, A, a):
    return A + a*np.cos(t)

In [151]: from scipy import optimize
    import time

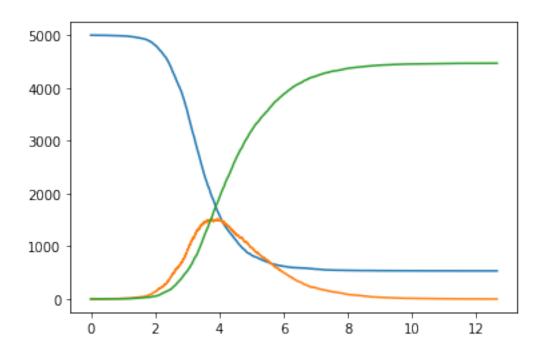
def exp_time_dependent_gillespie(tspan, X_0, f1_values, f2_values):

    def exp_contact_rate(t, A, a):
```

```
def solve_new_time(t, X, f1_values, f2_values, r):
    A = f1_values[0]
    a = f1_values[1]
    def f(x):
        return f2_{values*X[1]*x} + X[0]*X[1]*A*np.exp(-a*t)*(1 - np.exp(-a*x))/(Nexp(-a*x))
    return optimize.broyden1(f, [0.2], f_tol=1e-10)[0]
def calc_propensities(t, X, N, f1_values, f2_values):
    a1 = X[0]*X[1]*exp_contact_rate(t, f1_values[0], f1_values[1])/N
    # a_2: I \rightarrow R w/ rate gamma*I
    a2 = f2_values*X[1]
    return np.sum([a1, a2]), [a1, a2]
counter = 0
t_0, t_final = tspan
N = np.sum(X_0)
S = X_0[0]
I = X_0[1]
R = X_0[2]
S_hist = [S]
I_hist = [I]
R_{\text{hist}} = [R]
t_hist = [t_0]
t = t_0
X = X_0
prop_func = {}
prop_func[0] = np.array((-1,1,0)) # S + I -> I + I
prop_func[1] = np.array((0,-1,1)) # I \rightarrow R
while t < t_final:</pre>
    # generate new time
    r = np.random.rand()
    delta = solve_new_time(t, X, f1_values, f2_values, r)
    t = t + delta
    # calculate_propensities for updated time step
```

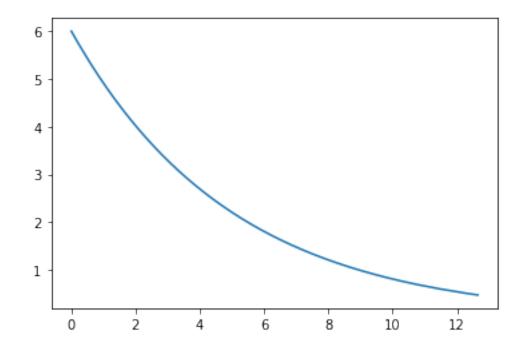
```
# choosing the reaction
                r = np.random.rand()
                a_list = a_list / a_0
                for k in range(len(a_list)):
                    if a_list[k] > r:
                        # reaction k chosen
                        break
                    else:
                        # reaction not chosen
                        pass
                X = X + prop_func[k]
                # record update
                S_hist.append(X[0])
                I_hist.append(X[1])
                R_hist.append(X[2])
                t_hist.append(t)
                counter += 1
                # check for extinction
                if X[1] == 0:
                    break
            print("="*50)
            print(" Basic Next Reaction Method for SIR Model")
            print(" Reaction 1: S + I -> I + I, with rate " + str(f1_values))
            print(" Total Number of Iterations in Simulation: " + str(counter))
            print("="*50)
            return S_hist, I_hist, R_hist, np.asarray(t_hist)
In [152]: S_hist, I_hist, R_hist, t_hist = exp_time_dependent_gillespie([0,20], [4999, 1, 0],
Basic Next Reaction Method for SIR Model
Reaction 1: S + I \rightarrow I + I, with rate [6, 0.2]
               I \rightarrow R , with rate 1
Reaction 2:
Total Number of Iterations in Simulation: 8933
_____
In [153]: plt.plot(t_hist, S_hist)
         plt.plot(t_hist, I_hist)
         plt.plot(t_hist, R_hist)
Out[153]: [<matplotlib.lines.Line2D at 0x2487bb74f98>]
```

a\_0, a\_list = calc\_propensities(t, X, N, f1\_values, f2\_values)



In [154]: plt.plot(t\_hist, 6\*np.exp(-0.2\*t\_hist))

Out[154]: [<matplotlib.lines.Line2D at 0x2487bbbfc18>]



## 0.3 2 - Cosine Contact Rate Model (Used in report)

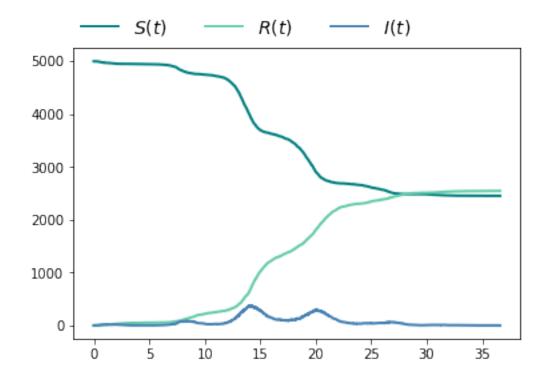
Please see the notebook titled "cosine\_contact\_model.ipynb" for further discussion and analysis.

```
B(t) = A + B\cos(t)
In [155]: def cos_time_dependent_gillespie(tspan, X_0, f1_values, f2_values):
              def cos_contact_rate(t, A, a):
                  return A + a*np.cos(t)
              def solve_new_time(t, X, f1_values, f2_values, r):
                  A = f1_values[0]
                  a = f1_values[1]
                  def f(x):
                       return f2_{values*X[1]*x} + (A*x + a*(np.sin(t)*np.cos(x) + np.sin(x)*np.cos(x))
                  return optimize.diagbroyden(f, [0.2], f_tol=1e-10)[0]
              def calc_propensities(t, X, N, f1_values, f2_values):
                   # a 1: S + I -> I + I  w/ rate B(t)*S*I/N
                  a1 = X[0]*X[1]*cos_contact_rate(t, f1_values[0], f1_values[1])/N
                   \# a_2: I \rightarrow R w/ rate gamma*I
                  a2 = f2_values*X[1]
                  return np.sum([a1, a2]), [a1, a2]
              counter = 0
              t_0, t_final = tspan
              N = np.sum(X_0)
              S = X_0[0]
              I = X_0[1]
              R = X_0[2]
              S_hist = [S]
              I_{hist} = [I]
              R_{hist} = [R]
              t_hist = [t_0]
              ss1 = []
              ss2 = []
              ss3 = []
```

 $t = t_0$ 

```
X = X_O
              prop_func = {}
              prop_func[0] = np.array((-1,1,0)) # S + I -> I + I
              prop_func[1] = np.array((0,-1,1)) # I \rightarrow R
              while t < t_final:</pre>
                  # generate new time
                  r = np.random.rand()
                  delta = solve_new_time(t, X, f1_values, f2_values, r)
                  t = t + delta
                  # calculate_propensities for updated time step
                  a_0, a_list = calc_propensities(t, X, N, f1_values, f2_values)
                  # choosing the reaction
                  r = np.random.rand()
                  a_list = a_list / a_0
                  for k in range(len(a_list)):
                      if a_list[k] > r:
                           # reaction k chosen
                           break
                      else:
                           # reaction not chosen
                          pass
                  X = X + prop_func[k] # perform the reaction
                  # record update
                  S_hist.append(X[0])
                  I_hist.append(X[1])
                  R_hist.append(X[2])
                  t_hist.append(t)
                  counter += 1
                  # check for extinction
                  if X[1] == 0 :
                      break
              return S_hist, I_hist, R_hist, np.asarray(t_hist)
In [156]: t_sim = 0
          while t_sim < 1:</pre>
```

Out[158]: <matplotlib.legend.Legend at 0x2487bc323c8>



In [157]: # saving the data for creating later figures
 import pickle
 with open("data/s\_sample\_cosine.pkl", "wb") as f:
 pickle.dump(S, f)

with open("data/i\_sample\_cosine.pkl", "wb") as f:
 pickle.dump(I, f)

```
with open("data/r_sample_cosine.pkl", "wb") as f:
           pickle.dump(R, f)
        with open("data/t_sample_cosine.pkl", "wb") as f:
           pickle.dump(t, f)
In []: # performing many simulations for many different infective introduction times
       WARNING
          - Takes a long time to run due to solver.
          - Produces a lot of data
          - Not optimal for sole purpose of looking at epidemic prob as gives full event his
      # this code was copied to Google Colab and run there due to better runtime.
      import time
      import pickle
      start = time.time()
      t_list = np.linspace(0, 20, 10)
      t_hist = {}
      counter = 17
      for t_0 in t_list:
          # test different R_O values
          t_hist[t_0] = {}
          t_hists = {}
          S_hists = {}
          I_hists = {}
          R_hists = {}
          for i in range(100):
             S, I, R, t = cos_time_dependent_gillespie([t_0, 100 + t_0], [9999, 1, 0], [1.4])
             t_hists[i] = t
             S_hists[i] = S
             I_hists[i] = I
             R_hists[i] = R
          fname_S = "s_hist_1.4_0.3_1000_counter_" + str(counter)+ ".pickle"
```

```
fname_I = "i_hist_1.4_0.3_1000_counter_" + str(counter)+ ".pickle"
            fname_R = "r_hist_1.4_0.3_1000_counter_" + str(counter)+ ".pickle"
            fname_t = "t_hist_1.4_0.3_1000_counter_" + str(counter)+ ".pickle"
            with open("data/" + fname_S, "wb") as f:
                pickle.dump(S_hists, f)
            with open("data/" + fname_I, "wb") as f:
                pickle.dump(I_hists, f)
            with open("data/" + fname_R, "wb") as f:
                pickle.dump(R_hists, f)
            with open("data/" + fname_t, "wb") as f:
                pickle.dump(t_hists, f)
            t_hist[t_0]["S"] = S_hists
            t_hist[t_0]["I"] = I_hists
            t_hist[t_0]["R"] = R_hists
            t_hist[t_0]["t"] = t_hists
            counter+=1
            print("Completed t="+str(t_0))
        end = time.time()
        print("Completed in :" + str(end - start))
In [ ]: # Finding lineages which we classify as Major Epidemics vs Minor
        # We say an epidemic is Major if the total number of infected over the duration of the
       major_epi = {}
       major_epi_threshold = 15
        for t_0 in t_list:
           major_epi[t_0] = []
            for i in range(len(t_hist[t_0]["R"])):
                total_infec = t_hist[t_0]["R"][i][-1]
                if total_infec > major_epi_threshold:
                    major_epi[t_0].append(1)
                else:
                    major_epi[t_0].append(0)
In [ ]: # Working out probabilities of Major epidemics from simulations
```

```
prob_list = []

for t_0 in t_list:
    major = np.sum(major_epi[t_0])
    total_sims = len(major_epi[t_0])
    print("="*100)
    print("t: "+ str(t_0))
    print("Simulation Probability: p(t) = " + str(1 - major / total_sims))
    prob_list.append(1 - major / total_sims)
    # print("Analytical Probability: " + str(max(0, 1- 1/t_0)))
    print("="*100)
In []:
```